A Bayesian Approach to Predicting NFL Player Scores in Fanduel Tournaments

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Purpose

The National Football League, NFL, is a professional American football league consisting of 32 teams. It is the most professional American football league in the world and is one of the most followed sports leagues in North America. Being a football fan, however, does not end with following matches on TV or stadiums or buying your favorite team's jersey. Over the years, football fans have come up with interesting NFL-themed side-activities, the most popular of which is called "Fantasy Football".

Participants in a **Fantasy Football** game act as the managers of a virtual football team and try to maximize their points by picking up the best line-up. Points are given based on actual performance of players in real-world competition. Each team is allowed a pre-determined number of players on its roster, as well as a specified number at each position that can or must be used in each game (the "starters").

For the purpose of this project, we have chosen to work with the data gathered from the **FanDuel** internet company. FanDuel is a web-based fantasy sports game and with 6 million registered users and is the second largest daily fantasy sports company (as measured by entry fees and user base) in the daily fantasy sports industry.

We will leverage a Hierarchical Bayesian approach with the Markov Chain Monte Carlo method to predict the Fantasy points likely to be scored by an NFL quarterback in any given game. The goal is to predict the points scored by each player given certain prior conditions and predictor variables that will assist our model in providing credible posterior prediction intervals. The following are the research questions that will be answered in this project:

- **Interpretation**: What features can help us effectively predict FanDuel points players receive in a future match?
- **Prediction**: How reliable are the predictions for the future performance of players?

Data

Historical data on the performance of the players is extracted from the **RotoGuru** website. Data scraped from RotoGuru includes information about the FanDuel points received by each player, player's position, player's opponent team, Home/Away match indication, etc. for each week.

The following is the code used to get the data from RotoGuru:

```
# Scrape rotoguru1 site for weekly FanDuel stats and bind each week's data to the
# pre-defined dataframe, 'd'.

for(year in 2014:2017){
  for(week in 1:16){
    page = read_html(
      gsub(" ","",
           paste("http://rotoguru1.com/cgi-bin/fyday.pl?week=",week,"&year=",
```

```
                year ,"&game=fd&scsv=1")
    ))
  dtext = page %>% html_nodes("pre") %>% html_text(trim = TRUE)
  dtable = read.table(text=dtext, sep = ";", header=TRUE, col.names = cnames,
                      quote=NULL)
  d = rbind(d,dtable)
 }
}
```

Data cleaning is performed using R routines. Some data cleaning tasks are needed to calculate Player rank.

Response Variables

- `FanDuelPts`: Points position at the end of a single game

Predictor Variables

- `AvgPts5Wks`: The 5 game average points of the player
- `AvgOppPAP7Wks` : The 7 game average Opposing Points Allowed to Position (OppPAP) by the current player's opposing defense. For example, if the Buffalo Bills defense allowed a total of 30 points per game to wide receivers for six games straight, then this number would equal to the average of 30 for any wide receiver facing the Bills defense.
- `Position`: The position the player plays
- `HomeGame`: Whether it is home game.
- `Rank`: The rank of a player based on recent performance

Sample Data

```
fdp <- read.csv("fdpfinal.csv", sep = ',', header = TRUE)

head(fdp)
```

```
##   Position Year YearWeek Opponent Week PlayerId             Name    Team
## 1       QB 2015   201513 Steelers   13     1060 Hasselbeck, Matt   Colts
## 2       QB 2015   201514  Jaguars   14     1060 Hasselbeck, Matt   Colts
## 3       QB 2015   201515   Texans   15     1060 Hasselbeck, Matt   Colts
## 4       QB 2015   201516 Dolphins   16     1060 Hasselbeck, Matt   Colts
## 5       QB 2015   201501   Ravens    1     1081  Manning, Peyton Broncos
## 6       QB 2015   201502   Chiefs    2     1081  Manning, Peyton Broncos
##   HomeGame FanDuelPts FanDuelSalary AvgOppPAP7Wks SdOppPAP7Wks OallAvgPAP
## 1        0       6.86          6500         20.95        8.045      17.44
## 2        0       9.08          6600         24.16        6.738      17.44
## 3        1       8.98          6400         16.36        9.690      17.44
## 4        0       3.96          6000         20.46        6.002      17.44
## 5        1       5.90          9100         18.99       11.697      17.44
## 6        0      21.24          8200         13.85        4.342      17.44
##   OallStdevPAP AvgPts5Wks StdevPts5Wks OffRnk5Wks DefRnk7Wks
## 1        2.909      14.85        4.824      Rank4      Rank1
## 2        2.909      14.82        4.897      Rank4      Rank1
```

```
## 3        2.909      13.56        5.490      Rank4      Rank3
## 4        2.909      12.11        5.566      Rank4      Rank2
## 5        2.909      14.96        8.496      Rank3      Rank1
## 6        2.909      10.53        5.011      Rank4      Rank4
```

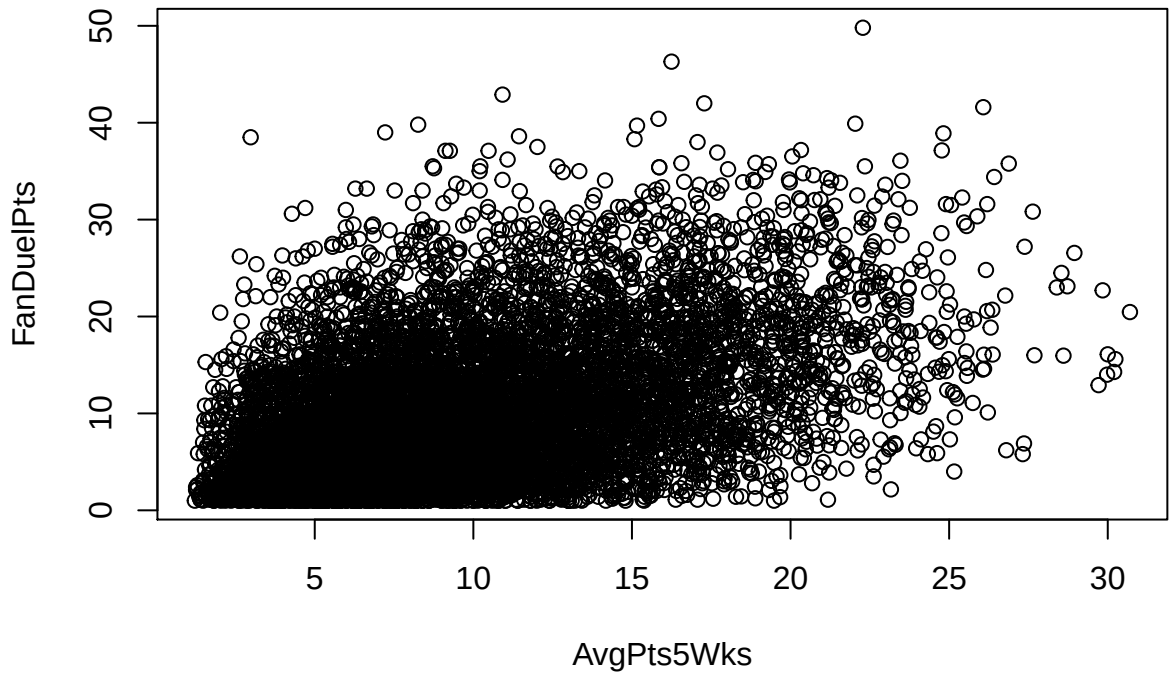
```
fdp['Rank'] = fdp$OffRnk5Wks
```

Simple LM graph

$y|\alpha \sim N(\alpha, \sigma_y^2 I)$

```
mod.classic = lm(FanDuelPts ~ AvgPts5Wks, data = fdp)

plot(FanDuelPts ~ AvgPts5Wks, data = fdp)
```



As can be seen from the graph above, the FanDuel data points are all over the place. The model proposed in the next section will present our approach to use the predictors.

Model

At the lowest level, we model the performance (`FanDuelPts`) as normally-distributed around a true value:

$y|\alpha, \beta_{defense}, \beta_{home}, \beta_{away}, \sigma_r^2 \sim N(\alpha + X_{defense}.\beta_{defense} + X_{home}.\beta_{home} + X_{away}.\beta_{away}, \sigma_y^2 I)$

where

α = The average fan duel point of the previous 5 weeks of the player, `AvgPts5Wks`

$\beta_{defense,p}$ = defense coefficient against team t for position p

$\beta_{home,p,r}$ = home coefficient for position p and a rank r player

$\beta_{away,p,r}$ = Away coefficient for position p and a rank r player

y = `FanDuelPts`

x_p = interaction indicator term for opposing team score allowed by position p

$x_{home,p,r}$ = interaction indicator term for rank r, position p, and whether it is home game

At the higher level, we model the defense effect, $\beta_{defense}$, as how well a particular team's defense has performed against the player's position. We pool the effect based on the position of the player. That is, the defense coefficient is normally distributed from the same position specific distribution.

$\beta_{defense,p} \sim N(\delta_p, \sigma_\delta^2)$

where σ_δ is constant = 1000

For the home and away game effect, β_{home} and β_{away}, we model the effect for player of the same rank has the same distribution. We model the home and away game effect to be the same for players of the same position.

$\beta_{home,p,r} \sim N(\eta_r, \sigma_\eta^2)$

$\beta_{away,p,r} \sim N(\rho_r, \sigma_\rho^2)$

where σ_η, σ_ρ are constant = 1000

We will approximate non informative prior using:

$\sigma_y \sim Inv - gamma(0.0001, 0.0001)$

$\delta \sim N(0, 10000^2)$

$\eta \sim N(0, 10000^2)$

$\rho \sim N(0, 10000^2)$

Note that in this project, we model the performance (`FanDuelPts`) as normally-distributed around a true value. Alternatively, we could have use Poisson distribution instead to avoid predicting the `FanDuelPts` less than zero. However, for the purpose of predicting player's `FanDuelPts`, we mainly only need the relative strength of players and the normal assumption produces good enough model. The portion of predicted `FanDuelPts` should be relatively small.

Here is the DAG model:

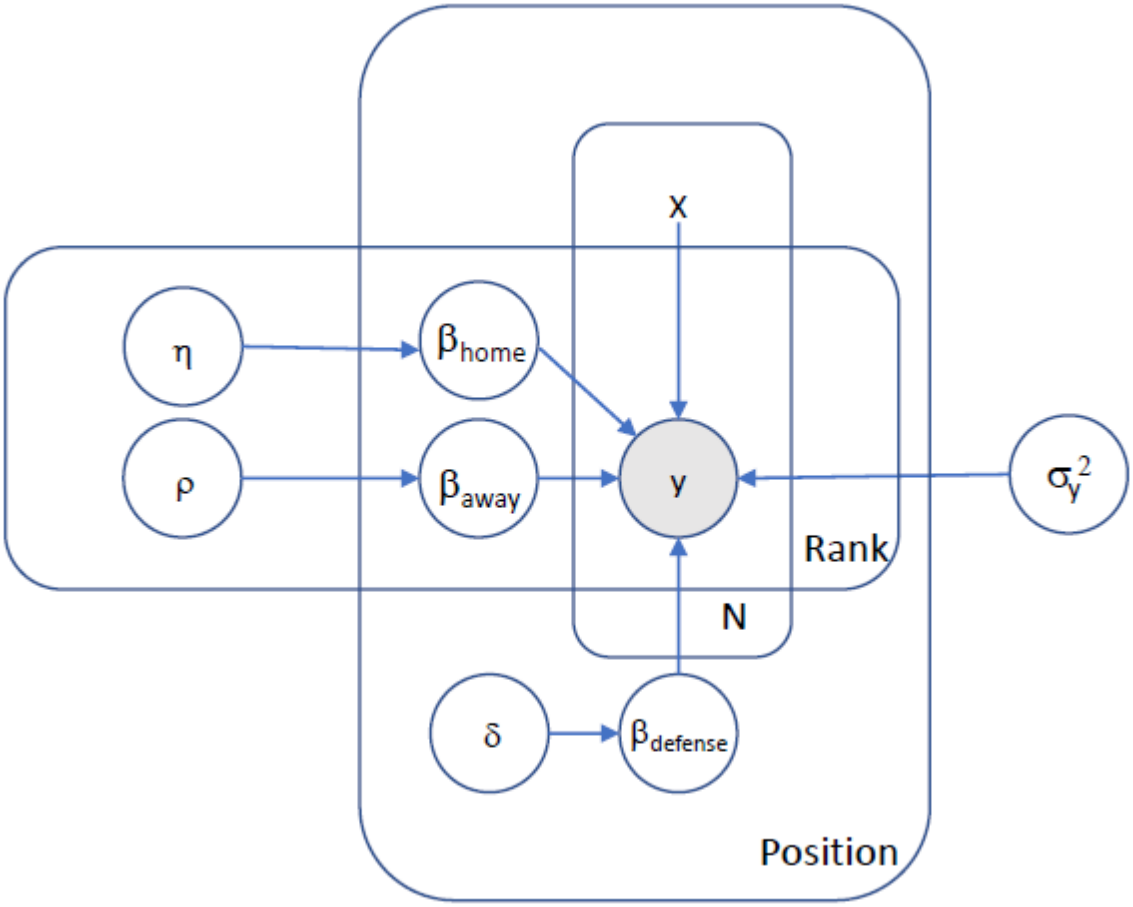


Figure 1: DAG model

Here is the JAGS model:

```
#sink("fdp.bug")
#cat("
model {
  for (i in 1:length(y)) {
    y[i] ~ dnorm(alpha[i] + inprod(X.defense[i, ], beta.defense)
                 + inprod(X.home[i, ], beta.home)
                 + inprod(X.away[i, ], beta.away), sigmasqinv)
  }

  # The entry of the beta.defense corresponds to Opponent:Position
  # In our model, we pool the beta.defense based on position.
  # i.e. All defense effects of the same position are drawn from the same distribution
  for (p in 1:Num.Position) {
    for (f in 1:Num.fixed.pred) {
      beta.defense[(f-1) * Num.Position + p] ~ dnorm(delta[p], 1/1000^2)
      delta[(f-1) * Num.Position + p] ~ dnorm(0, 1/100000^2)
    }
  }

  # The entry of the beta.home and beta.away corresponds to Rank:Position
  # In our model, we pool the beta.home/away based on rank
  for (r in 1:Num.Rank) {
    for (t in 1:Num.Position) {
      beta.home[(t-1) * Num.Rank + r] ~ dnorm(eta[r], 1/1000^2)
      beta.away[(t-1) * Num.Rank + r] ~ dnorm(rho[r], 1/1000^2)
    }
    eta[r] ~ dnorm(0, 1/100000^2)
    rho[r] ~ dnorm(0, 1/100000^2)
  }

  sigmasqinv ~ dgamma(0.0001, 0.0001)
  sigmasq <- 1/sigmasqinv
}
#    ",fill = TRUE)
#sink()
```

Computation

We use overdispersed starting points and 4 chains to initialized. We have seen slow mix in and hence we use thinning of 5 to get a smaller number of data points. Convergence diagnostics are performed graphically as well as using Gelman Statistics. We make sure sample size are > 400. The Monte Carlo error of the β are less than 0.06, but the ones of the hyper parameters are much higher at around 5.

Training Data Setup

Due to significant roster change usually happens in the off-season, we believe it is the best to not use data across seasons. We use 2016 data as it is the most recent year with a full season. We set aside the last week for verifying prediction accuracy of the model.

```
#fdp_train=fdp[fdp$Year == 2015, ]
fdp_train=fdp[fdp$Year == 2016  & ((fdp$Position == "QB"& fdp$FanDuelSalary > 6500 & !is.na(fdp$FanDuel
#fdp_train=fdp[fdp$Year == 2015 & (fdp$Position == "QB" | fdp$Position == "RB") & fdp$FanDuelSalary > 6

fdp_test =fdp_train[fdp_train$YearWeek >= 201615, ]
fdp_test = droplevels(fdp_test)
fdp_train=fdp_train[fdp_train$YearWeek < 201615, ]
fdp_train = droplevels(fdp_train)
```

```
Use.Rank = TRUE
Num.Opponent = length(unique(fdp_train[, "Opponent"]))
Num.Position = length(unique(fdp_train[, "Position"]))
#Num.fixed.pred=2 #AvgOppPAP7Wks + FanDuelSalary
Num.fixed.pred=1 #AvgOppPAP7Wks
if (Use.Rank) {
  Num.Rank = length(unique(fdp_train[, "Rank"]))
  Num.HomeAwayInit = Num.Rank
  Model.File.Ext = ""
} else {
  Num.HomeAwayInit = 1
  Model.File.Ext = ".norank"
}


if (Num.Position == 1) {
  #X.defense = model.matrix(~ 0 + AvgOppPAP7Wks + FanDuelSalary, data=fdp_train)
  X.defense = model.matrix(~ 0 + AvgOppPAP7Wks, data=fdp_train)
  if (Use.Rank) {
    X.home = model.matrix(~ 0 + Rank , data=fdp_train)
    X.away = model.matrix(~ 0 + Rank , data=fdp_train)
  } else {
    X.home = rep(1, nrow(fdp_train))
    X.away = rep(1, nrow(fdp_train))
  }
} else {
  #X.defense = model.matrix(~ 0 + AvgOppPAP7Wks:Position + FanDuelSalary:Position, data=fdp_train)
  X.defense = model.matrix(~ 0 + AvgOppPAP7Wks:Position, data=fdp_train)
  if (Use.Rank) {
    X.home = model.matrix(~ 0 + Rank:Position , data=fdp_train)
```

```
    X.away = model.matrix(~ 0 + Rank:Position , data=fdp_train)
  } else {
    X.home = model.matrix(~ 0 + Position , data=fdp_train)
    X.away = model.matrix(~ 0 + Position , data=fdp_train)
  }
}


X.home = X.home * fdp_train$HomeGame
X.away = X.away * (1- fdp_train$HomeGame)
X = cbind(X.defense, X.home, X.away)
```

The following code set up the data used in the model computation. `X.defense` captures the interaction terms between the defensive power (higher `AvgOppPAP7Wks` means the player is facing a weaker team, since they allows players score more point on them) and position.

Sample X.defense

```
head(X.defense)
```

```
##    AvgOppPAP7Wks:PositionPK AvgOppPAP7Wks:PositionQB
## 28                        0                    19.19
## 29                        0                    17.59
## 30                        0                    15.92
## 31                        0                    13.18
## 32                        0                    16.09
## 33                        0                    19.19
```

`X.home` and `X.away` are the interaction terms between Position and Rank. Together `X.home` and `X.away` will always sum to one. The intercept is implicitly included.

Sample X.home

```
head(X.home)
```

```
##    RankRank1:PositionPK RankRank2:PositionPK RankRank3:PositionPK
## 28                    0                    0                    0
## 29                    0                    0                    0
## 30                    0                    0                    0
## 31                    0                    0                    0
## 32                    0                    0                    0
## 33                    0                    0                    0
##    RankRank4:PositionPK RankRank1:PositionQB RankRank2:PositionQB
## 28                    0                    0                    0
## 29                    0                    1                    0
## 30                    0                    0                    0
## 31                    0                    0                    0
## 32                    0                    1                    0
## 33                    0                    0                    0
##    RankRank3:PositionQB RankRank4:PositionQB
## 28                    0                    0
## 29                    0                    0
## 30                    0                    0
```

```
## 31                    0                    0
## 32                    0                    0
## 33                    0                    0
```

Initialization

```
# Initialization List for the 4 chains
jags.inits=list(
  list( sigmasqinv=    0.01,  delta = rep(-100000, Num.Position * Num.fixed.pred),
        eta = c(100000, -100000, 100000, -100000)[1:Num.HomeAwayInit],
        rho = c(-100000, 100000, -100000, 100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 ),
  list( sigmasqinv=    0.01,  delta = rep(100000, Num.Position * Num.fixed.pred),
        eta = c(100000, -100000, -100000, 100000)[1:Num.HomeAwayInit],
        rho = c(-100000, 100000, 100000, -100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 + 1 ),
  list( sigmasqinv=0.000001,  delta = rep(-100000, Num.Position * Num.fixed.pred),
        eta = c(-100000, 100000, -100000, 100000)[1:Num.HomeAwayInit],
        rho = c(100000, -100000, 100000, -100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 + 2 ),
  list( sigmasqinv=0.000001,  delta = rep(100000, Num.Position * Num.fixed.pred),
        eta = c(-100000, 100000, 100000, -100000)[1:Num.HomeAwayInit],
        rho = c(100000, -100000, -100000, 100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 + 3 )
)

data.jags <- list(
  y= fdp_train$FanDuelPts,
  alpha = fdp_train$AvgPts5Wks,
  X.defense = X.defense,
  X.home = X.home,
  X.away = X.away,
  Num.fixed.pred=Num.fixed.pred,
  Num.Position=Num.Position,
  #Num.Opponent=Num.Opponent,
  Num.Rank=Num.Rank
)
```

```
burnAndSample = function(m, N.burnin, N.iter, show.plot, mon.col, n.thin=1) {
  update(m, N.burnin) # burn-in

  x <- coda.samples(m, mon.col, n.iter=N.iter, n.thin)

  if(show.plot) {
    plot(x, smooth=FALSE)
  }

  gelman.R = gelman.diag(x, autoburnin=FALSE, multivariate = FALSE)

  result <- list(
    coda.sam = x,
    gelman.R.max=max(gelman.R$psrf[, 1]),
```

```
    gelman.R = gelman.R
  )

  return(result)
}
```

```
runModel=TRUE
runSample=TRUE

mon.col <- c("delta", "eta", "rho", "beta.defense", "beta.home", "beta.away", "sigmasq")

NSim = 30000
NChain = 4
NThin = 5
NTotalSim = NSim * NChain / 5
if (runModel) {
  m <- jags.model("fdp.bug", data.jags, inits = jags.inits, n.chains=NChain, n.adapt = 1000)
  save(file=paste("fdp.jags.model.init", Model.File.Ext, ".Rdata", sep=""), list="m")
} else {
  load(paste("fdp.jags.model.init", Model.File.Ext, ".Rdata", sep=""))
  m$recompile()
}
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 746
##    Unobserved stochastic nodes: 29
##    Total graph size: 18345
##
## Initializing model
```

```
load.module("dic")
```

```
## module dic loaded
```

```
N.Retry.Loop = 1
if (runSample) {
  N.burnin=2500/2
  for (loopIdx in 1:N.Retry.Loop) {
    (start_time <- Sys.time())
    (N.burnin = N.burnin * 2)
    result = burnAndSample(m, N.burnin, NSim, show.plot=FALSE, mon.col = mon.col, n.thin=NChain)
    (end_time <- Sys.time())
    (result$gelman.R.max)
  }
  run.params = paste(".", N.burnin, ".", NChain, ".", NSim, ".", NThin, sep="")
  save(file=paste("fdp.jags.samples", run.params, Model.File.Ext, ".Rdata", sep=""), list="result")
  save(file=paste("fdp.jags.model", run.params, Model.File.Ext, ".Rdata", sep=""), list="m")
} else {
  N.burnin=2500/2 * (2**N.Retry.Loop)
```

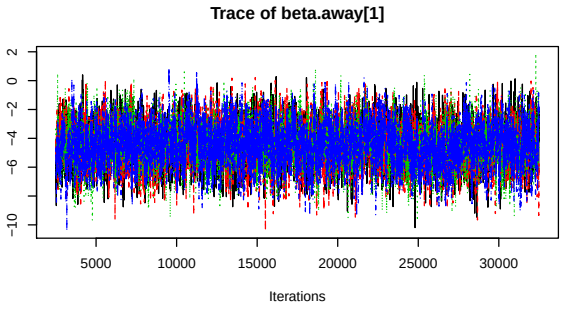
```
  run.params = paste(".", N.burnin, ".", NChain, ".", NSim, ".", NThin, sep="")
  load(paste("fdp.jags.samples", run.params, Model.File.Ext, ".Rdata", sep=""))
  load(paste("fdp.jags.model", run.params, Model.File.Ext, ".Rdata", sep=""))
  m$recompile()
}
```

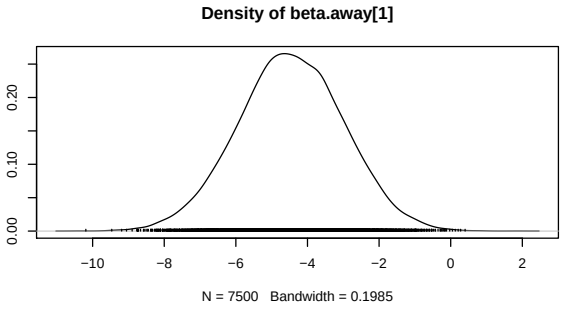
Convergence diagnostics

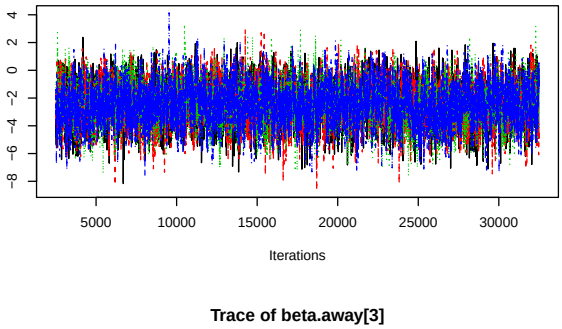
Trace Plots

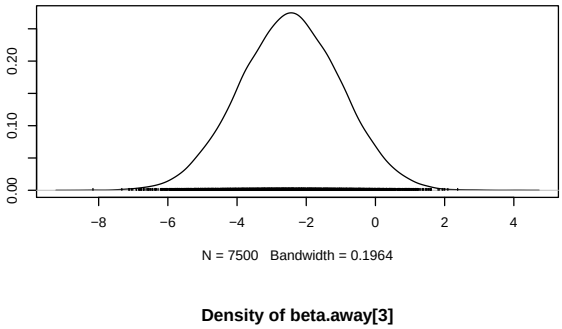
The trace plots of all parameters show good distribution convergence.

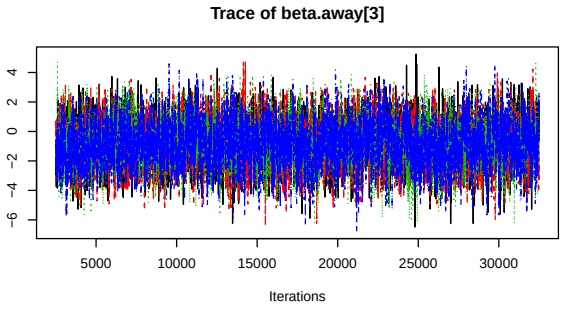
```
plot(result$coda.sam, smooth=FALSE)
```

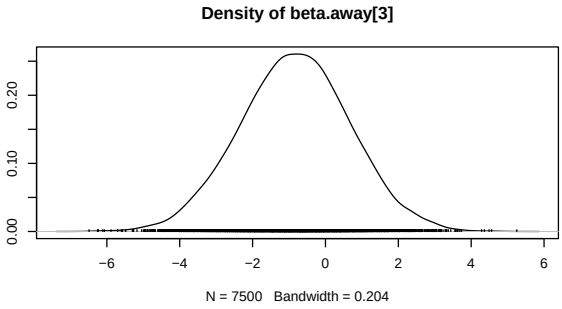

Trace of beta.away[1]
Iterations

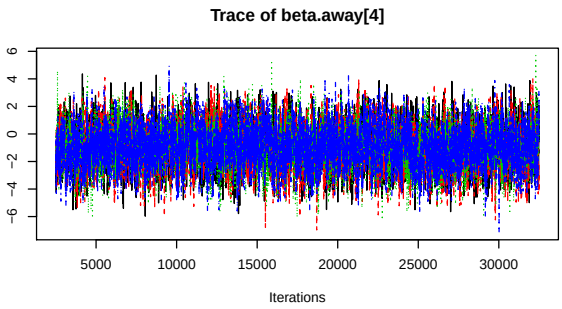

Density of beta.away[1]
N = 7500 Bandwidth = 0.1985

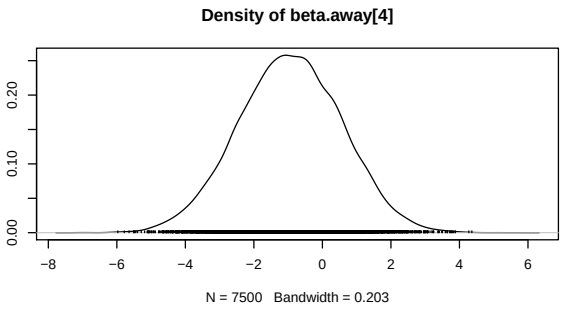

Trace of beta.away[2]
Iterations

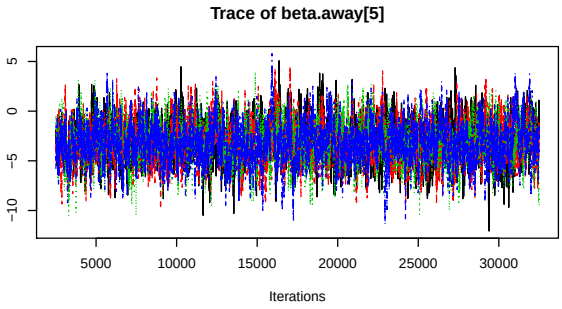

Density of beta.away[2]
N = 7500 Bandwidth = 0.1964

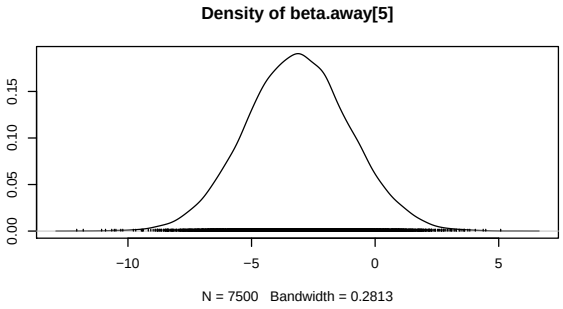

Trace of beta.away[3]
Iterations

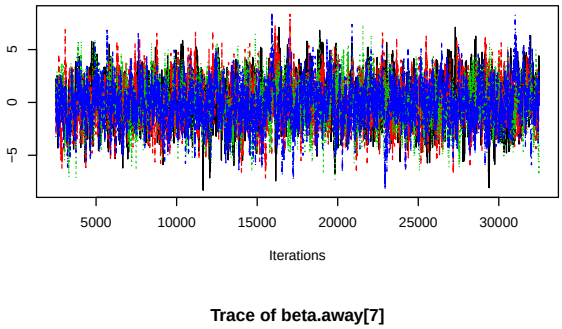

Density of beta.away[3]
N = 7500 Bandwidth = 0.204

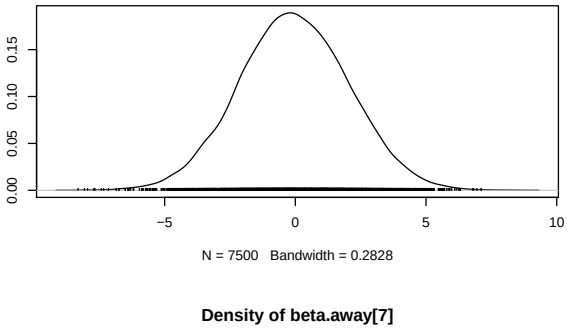

Trace of beta.away[4]
Iterations

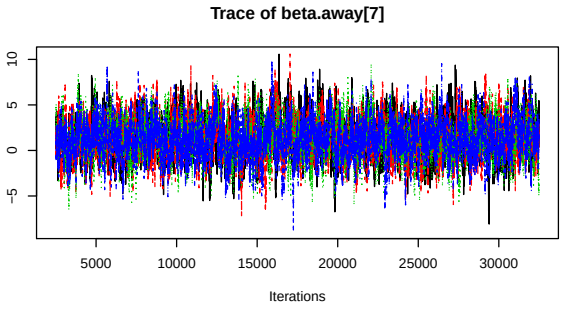

Density of beta.away[4]
N = 7500 Bandwidth = 0.203

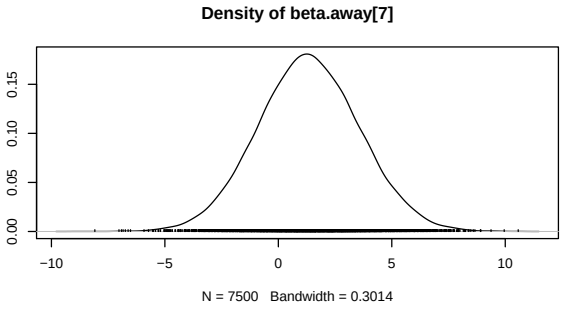

Trace of beta.away[5]
Iterations


Density of beta.away[5]
N = 7500 Bandwidth = 0.2813


Trace of beta.away[6]
Iterations


Density of beta.away[6]
N = 7500 Bandwidth = 0.2828


Trace of beta.away[7]
Iterations


Density of beta.away[7]
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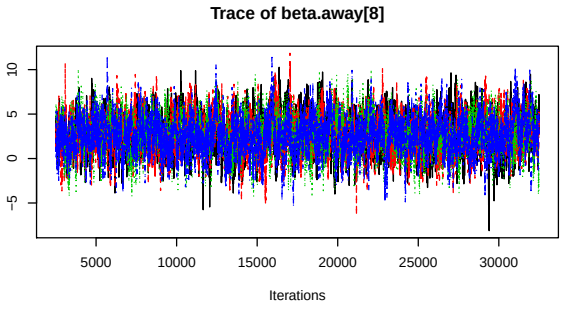
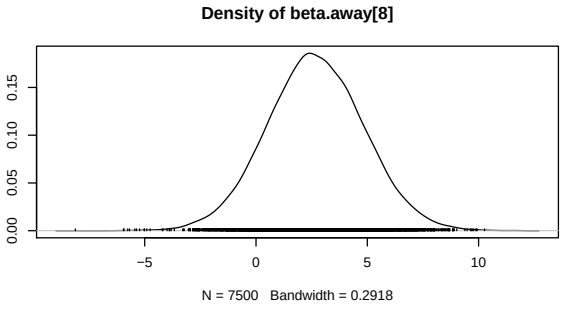
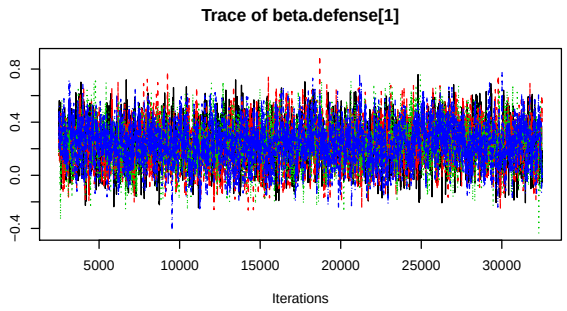
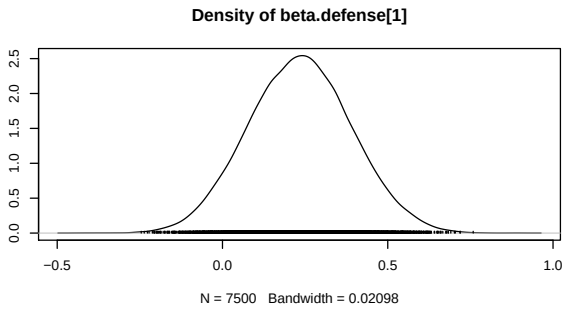
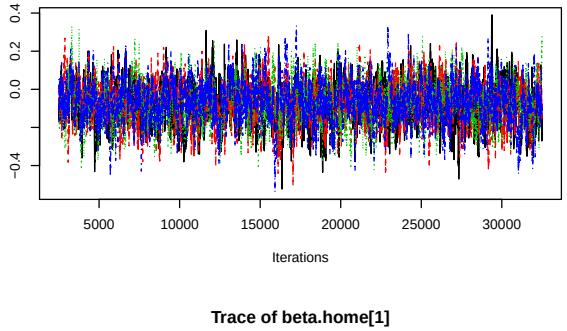
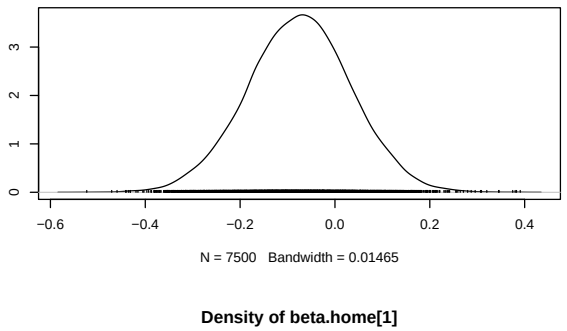

Trace of beta.away[8]
Iterations


Density of beta.away[8]
N = 7500 Bandwidth = 0.2918


Trace of beta.defense[1]
Iterations


Density of beta.defense[1]
N = 7500 Bandwidth = 0.02098


Trace of beta.defense[2]
Iterations


Density of beta.defense[2]
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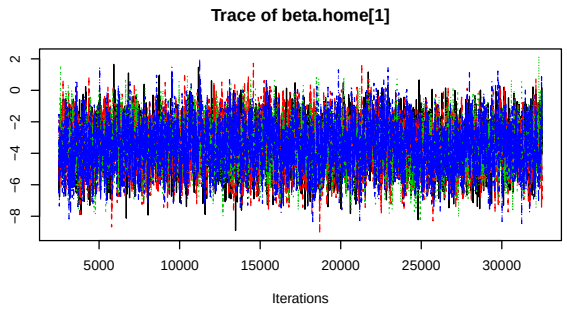
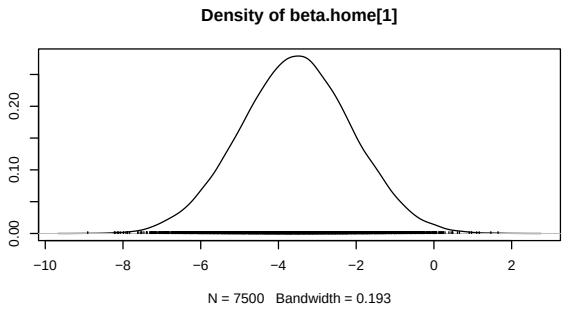
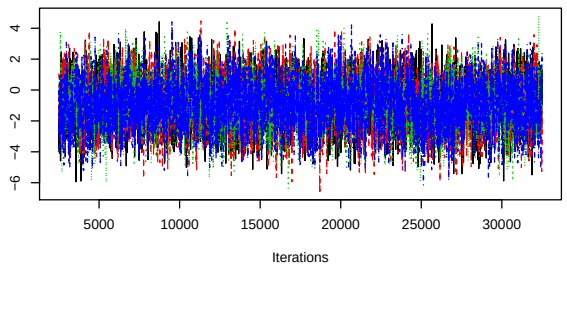
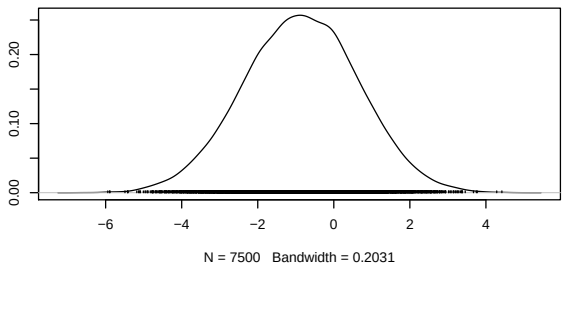
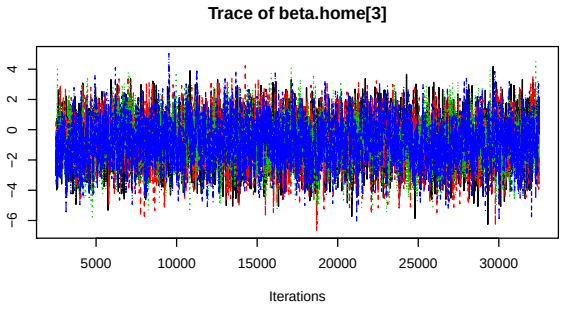
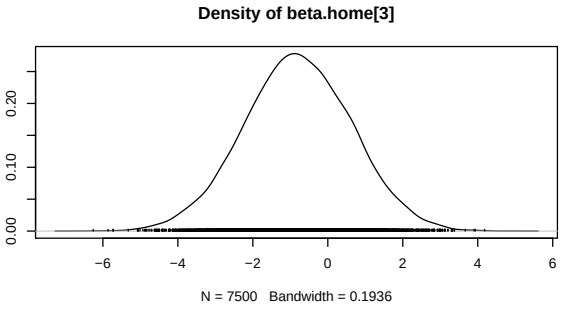

Trace of beta.home[1]
Iterations

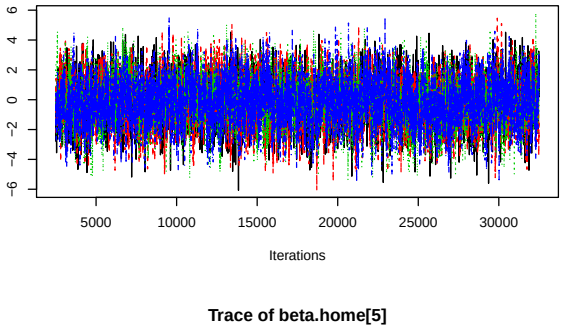

Density of beta.home[1]
N = 7500 Bandwidth = 0.193

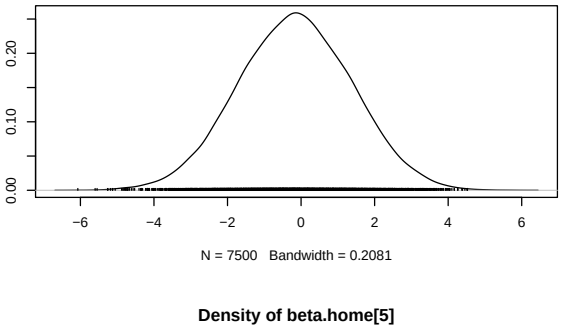

Trace of beta.home[2]
Iterations

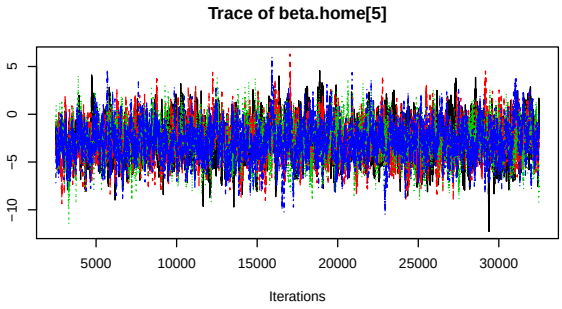

Density of beta.home[2]
N = 7500 Bandwidth = 0.2031

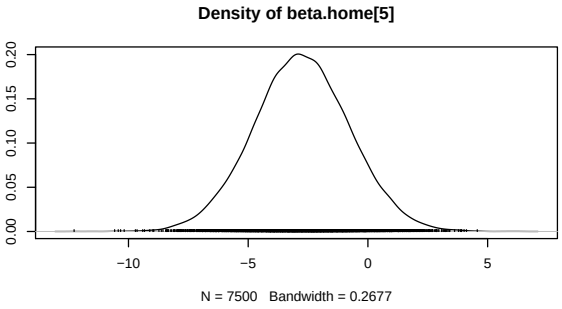

Trace of beta.home[3]
Iterations

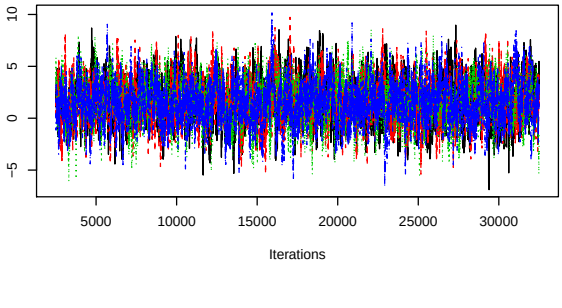

Density of beta.home[3]
N = 7500 Bandwidth = 0.1936

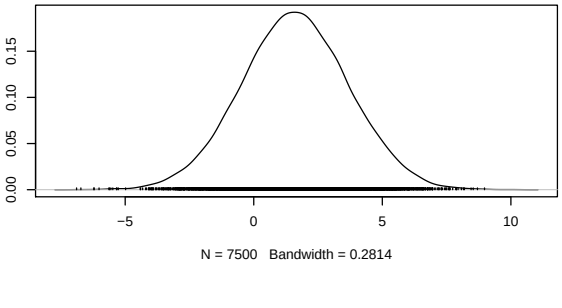

Trace of beta.home[4]
Iterations

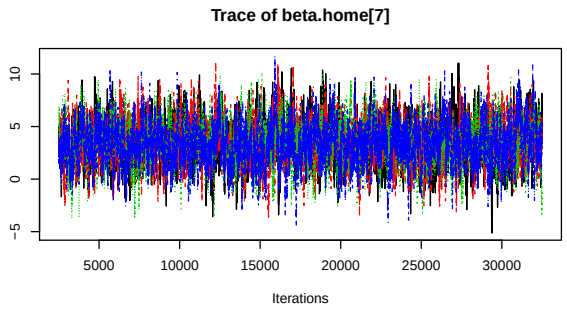

Density of beta.home[4]
N = 7500 Bandwidth = 0.2081

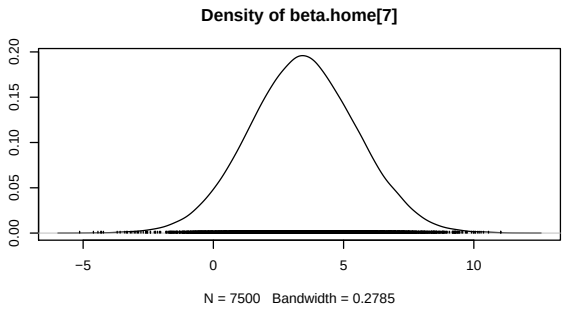

Trace of beta.home[5]
Iterations

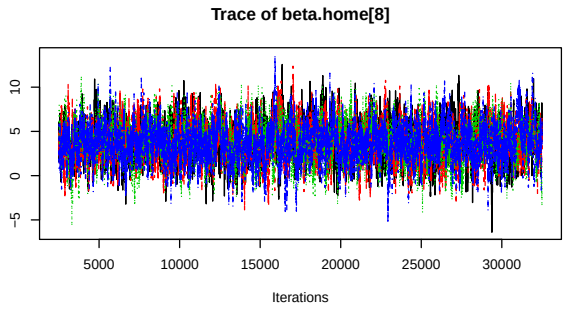

Density of beta.home[5]
N = 7500 Bandwidth = 0.2677

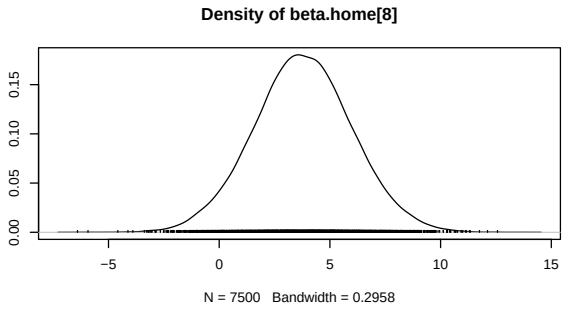

Trace of beta.home[6]
Iterations

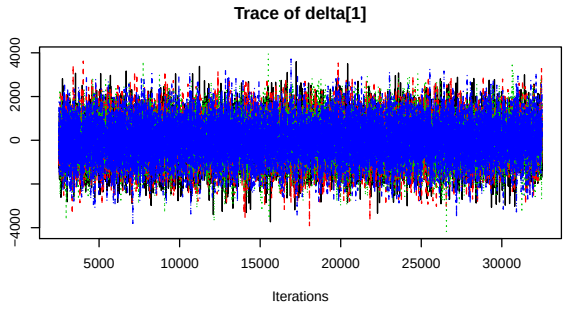

Density of beta.home[6]
N = 7500 Bandwidth = 0.2814

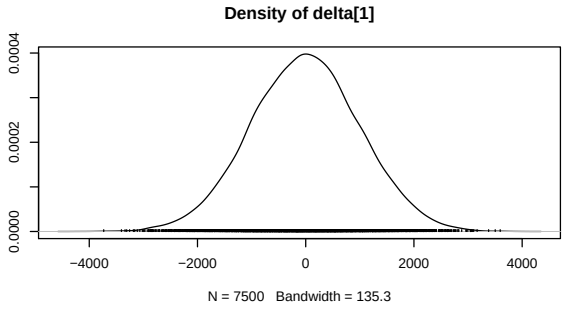

Trace of beta.home[7]
Iterations

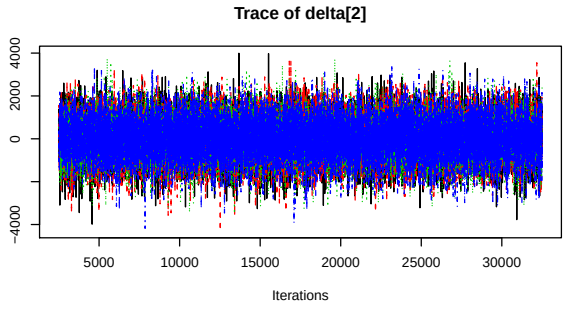

Density of beta.home[7]
N = 7500 Bandwidth = 0.2785

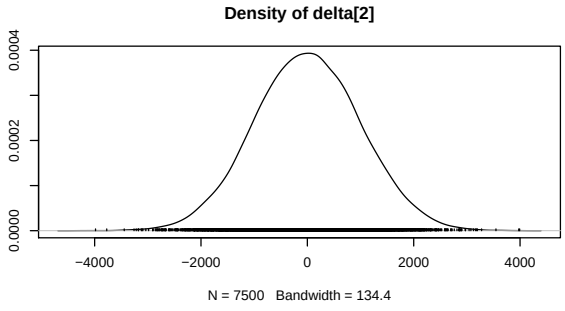

Trace of beta.home[8]
Iterations

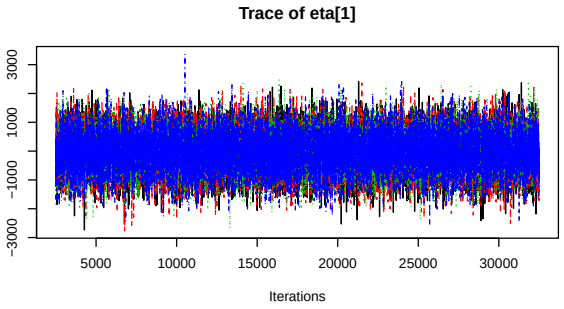

Density of beta.home[8]
N = 7500 Bandwidth = 0.2958

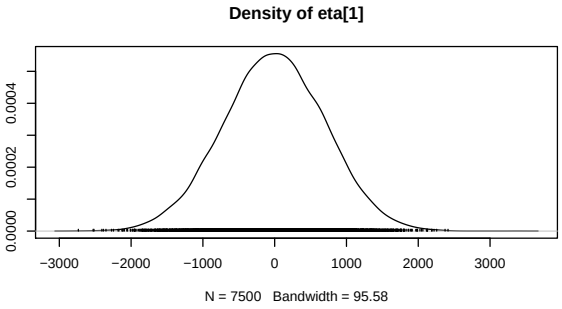

Trace of delta[1]
Iterations

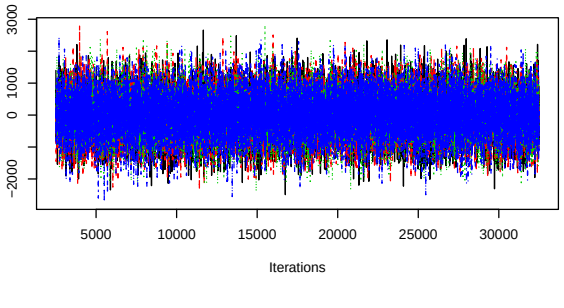

Density of delta[1]
N = 7500 Bandwidth = 135.3

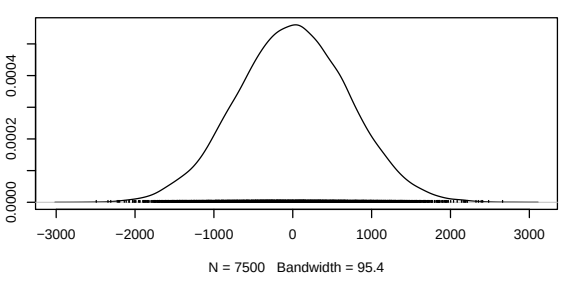

Trace of delta[2]
Iterations

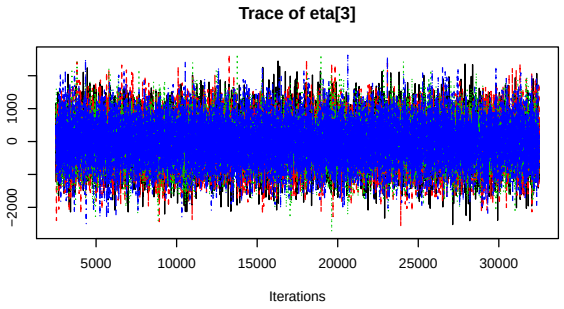

Density of delta[2]
N = 7500 Bandwidth = 134.4

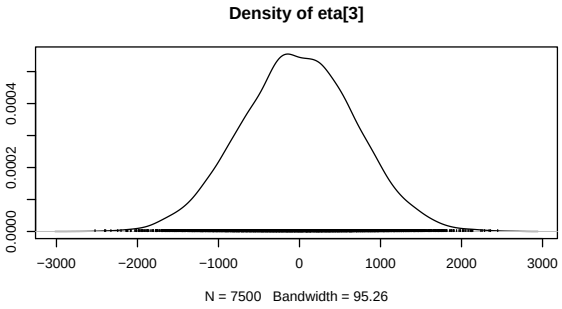

Trace of eta[1]
Iterations

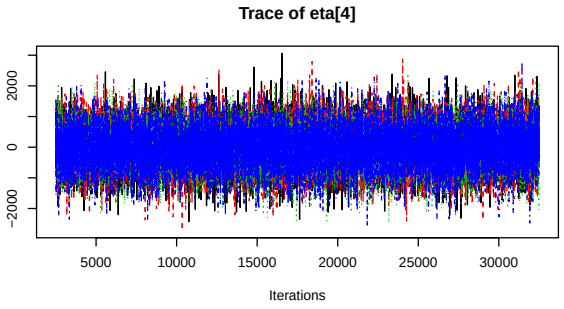

Density of eta[1]
N = 7500 Bandwidth = 95.58

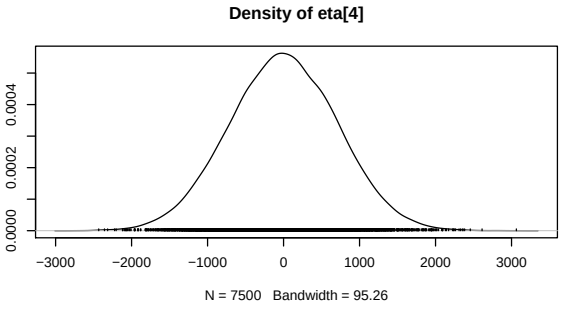

Trace of eta[2]
Iterations

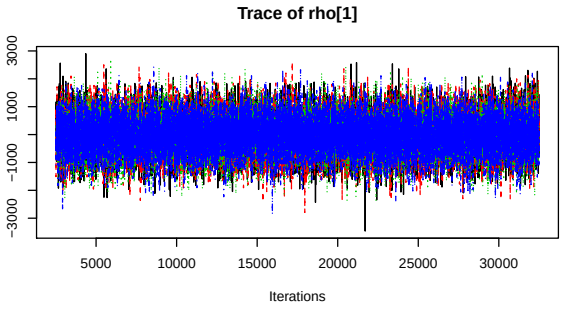

Density of eta[2]
N = 7500 Bandwidth = 95.4


Trace of eta[3]
Iterations


Density of eta[3]
N = 7500 Bandwidth = 95.26


Trace of eta[4]
Iterations


Density of eta[4]
N = 7500 Bandwidth = 95.26


Trace of rho[1]
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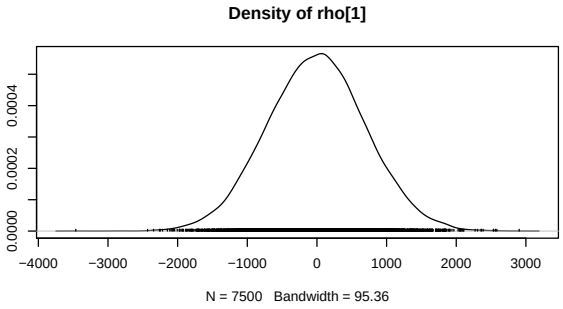
1000
−1000
−3000
5000
10000
15000
20000
25000
30000
Iterations


Density of rho[1]
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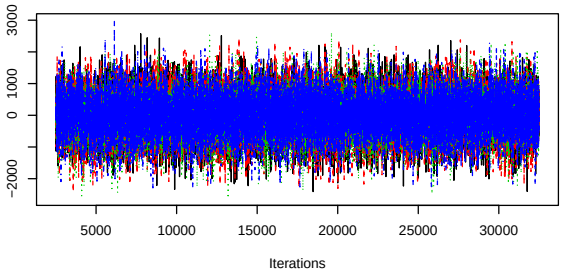
0.0002
0.0000
−4000
−3000
−2000
−1000
0
1000
2000
3000
N = 7500 Bandwidth = 95.36


Trace of rho[2]
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1000
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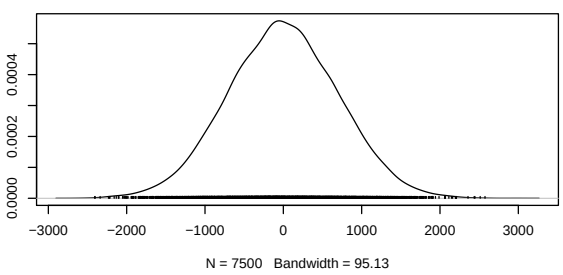
5000
10000
15000
20000
25000
30000
Iterations


Density of rho[2]
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−2000
−1000
0
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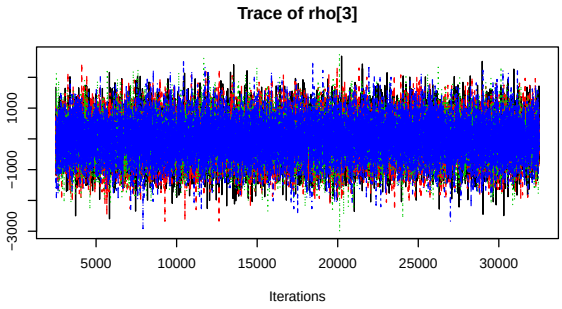
2000
3000
N = 7500 Bandwidth = 95.13


Trace of rho[3]
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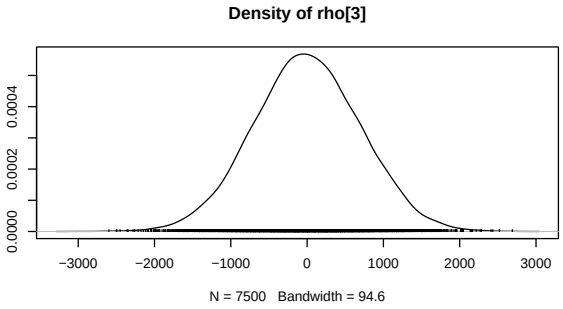
5000
10000
15000
20000
25000
30000
Iterations


Density of rho[3]
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0.0002
0.0000
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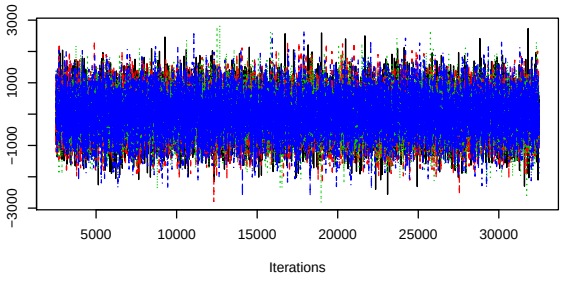
−2000
−1000
0
1000
2000
3000
N = 7500 Bandwidth = 94.6


Trace of rho[4]
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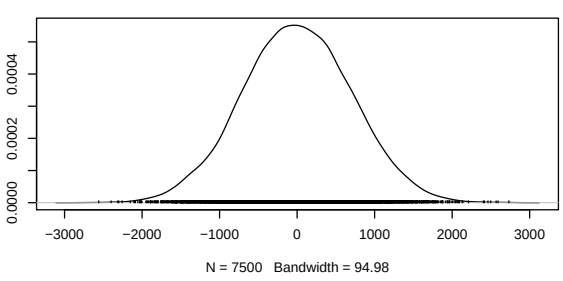
−3000
5000
10000
15000
20000
25000
30000
Iterations


Density of rho[4]
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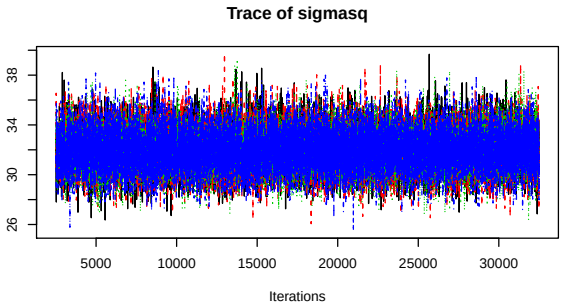
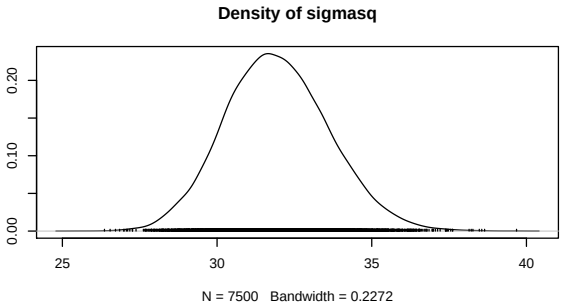
0
1000
2000
3000
N = 7500 Bandwidth = 94.98





Gelman Statistics

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result$gelman.R
```

```
## Potential scale reduction factors:
##
##                 Point est. Upper C.I.
## beta.away[1]             1       1.00
```

```
## beta.away[2]             1       1.00
## beta.away[3]             1       1.00
## beta.away[4]             1       1.00
## beta.away[5]             1       1.01
## beta.away[6]             1       1.01
## beta.away[7]             1       1.00
## beta.away[8]             1       1.01
## beta.defense[1]          1       1.00
## beta.defense[2]          1       1.01
## beta.home[1]             1       1.00
## beta.home[2]             1       1.00
## beta.home[3]             1       1.00
## beta.home[4]             1       1.00
## beta.home[5]             1       1.00
## beta.home[6]             1       1.01
## beta.home[7]             1       1.01
## beta.home[8]             1       1.01
## delta[1]                 1       1.00
## delta[2]                 1       1.00
## eta[1]                   1       1.00
## eta[2]                   1       1.00
## eta[3]                   1       1.00
## eta[4]                   1       1.00
## rho[1]                   1       1.00
## rho[2]                   1       1.00
## rho[3]                   1       1.00
## rho[4]                   1       1.00
## sigmasq                  1       1.00
```

Converged as `gelman.R.max` $= 1.002 < 1.1$ and the plot also looks good.

MCMC Summary

```
(m.summary = summary(result$coda.sam))
```

```
##
## Iterations = 2504:32500
## Thinning interval = 4
## Number of chains = 4
## Sample size per chain = 7500
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                   Mean       SD Naive SE Time-series SE
## beta.away[1]    -4.467    1.472 0.008499        0.02417
## beta.away[2]    -2.461    1.456 0.008408        0.02444
## beta.away[3]    -0.832    1.513 0.008733        0.02360
## beta.away[4]    -0.942    1.505 0.008691        0.02398
## beta.away[5]    -3.132    2.096 0.012100        0.05062
## beta.away[6]    -0.051    2.097 0.012108        0.05033
## beta.away[7]     1.343    2.235 0.012903        0.05291
```

```
## beta.away[8]     2.670    2.175 0.012558        0.05066
## beta.defense[1]  0.235    0.156 0.000898        0.00285
## beta.defense[2] -0.075    0.109 0.000632        0.00283
## beta.home[1]    -3.547    1.431 0.008264        0.02330
## beta.home[2]    -0.859    1.506 0.008694        0.02329
## beta.home[3]    -0.805    1.435 0.008287        0.02291
## beta.home[4]    -0.162    1.543 0.008909        0.02516
## beta.home[5]    -2.767    2.006 0.011579        0.04770
## beta.home[6]     1.605    2.086 0.012045        0.04957
## beta.home[7]     3.449    2.074 0.011976        0.04888
## beta.home[8]     3.784    2.221 0.012826        0.05233
## delta[1]        -6.780 1003.390 5.793077        5.89868
## delta[2]         1.764  996.816 5.755122        5.75533
## eta[1]          -7.966  708.771 4.092093        4.08607
## eta[2]           2.218  707.396 4.084150        4.08699
## eta[3]          -9.512  706.400 4.078403        4.05872
## eta[4]          -1.529  706.367 4.078209        4.02323
## rho[1]          -6.188  707.088 4.082376        4.10605
## rho[2]          -3.301  705.424 4.072770        4.11118
## rho[3]          -1.886  701.548 4.050388        4.05048
## rho[4]           1.520  704.309 4.066333        4.04433
## sigmasq         31.947    1.685 0.009727        0.00974
##
## 2. Quantiles for each variable:
##
##                       2.5%      25%      50%       75%    97.5%
## beta.away[1]       -7.3717   -5.453  -4.4688  -3.46981   -1.611
## beta.away[2]       -5.3105   -3.446  -2.4545  -1.46614    0.366
## beta.away[3]       -3.8050   -1.845  -0.8234   0.18547    2.160
## beta.away[4]       -3.8988   -1.965  -0.9387   0.09424    1.969
## beta.away[5]       -7.2309   -4.542  -3.1370  -1.74709    1.026
## beta.away[6]       -4.1378   -1.461  -0.0690   1.36573    4.063
## beta.away[7]       -3.0093   -0.157   1.3282   2.84138    5.776
## beta.away[8]       -1.5793    1.223   2.6498   4.12313    6.979
## beta.defense[1]    -0.0663    0.129   0.2350   0.33995    0.543
## beta.defense[2]    -0.2931   -0.148  -0.0741  -0.00196    0.138
## beta.home[1]       -6.3655   -4.514  -3.5414  -2.58559   -0.756
## beta.home[2]       -3.8301   -1.887  -0.8491   0.16783    2.062
## beta.home[3]       -3.6558   -1.769  -0.8066   0.17242    2.007
## beta.home[4]       -3.1788   -1.211  -0.1571   0.88799    2.859
## beta.home[5]       -6.6877   -4.098  -2.7803  -1.43849    1.176
## beta.home[6]       -2.4894    0.204   1.5977   3.00227    5.706
## beta.home[7]       -0.5994    2.064   3.4377   4.83181    7.517
## beta.home[8]       -0.6143    2.315   3.7747   5.25484    8.181
## delta[1]        -1978.4088 -688.037  -4.1092 662.68424 1965.061
## delta[2]        -1940.6629 -675.923  -2.0463 671.92029 1962.165
## eta[1]          -1413.8970 -482.575  -5.4483 474.92512 1370.112
## eta[2]          -1394.8328 -476.146   1.7122 481.47216 1388.076
## eta[3]          -1396.0830 -483.186  -9.9967 470.21005 1376.652
## eta[4]          -1382.7089 -479.828  -1.6793 479.87624 1378.586
## rho[1]          -1387.9001 -483.225  -2.6988 464.93505 1388.009
## rho[2]          -1382.8577 -480.359  -6.9693 470.32306 1373.230
## rho[3]          -1376.5466 -471.454  -6.5531 468.53942 1366.468
## rho[4]          -1383.8694 -474.965  -1.9381 476.58238 1379.023
```

```
## sigmasq            28.7819   30.779  31.8832  33.05067   35.406
```

Effective Sample Size

```
(eff.size = effectiveSize(result$coda.sam[, ]))
```

```
##    beta.away[1]    beta.away[2]    beta.away[3]    beta.away[4]    beta.away[5]
##            3711            3557            4146            3985            1718
##    beta.away[6]    beta.away[7]    beta.away[8] beta.defense[1] beta.defense[2]
##            1736            1787            1849            2988            1497
##    beta.home[1]    beta.home[2]    beta.home[3]    beta.home[4]    beta.home[5]
##            3792            4202            3943            3788            1767
##    beta.home[6]    beta.home[7]    beta.home[8]        delta[1]        delta[2]
##            1773            1805            1817           29040           30000
##          eta[1]          eta[2]          eta[3]          eta[4]          rho[1]
##           30088           29956           30305           30853           29666
##          rho[2]          rho[3]          rho[4]         sigmasq
##           29489           30000           30441           29940
```

The effective sample sizes of all parameters are greater than 400.

Model Assessment

General posterior model assumption check

Probabiliy of players should perform better at home than away

```
post.samp = as.matrix(result$coda.sam)

beta.home = post.samp[, paste("beta.home[",1:(Num.Rank*Num.Position),"]", sep="")]
beta.away = post.samp[, paste("beta.away[",1:(Num.Rank*Num.Position),"]", sep="")]

prob.home.away = rep(0, Num.Rank * Num.Position)
for (r in 1:Num.Rank) {
  for (p in 1:Num.Position) {
    idx = (p-1) * Num.Rank + r
    prob.home.away[idx] = mean(beta.home[, idx] > beta.away[, idx])
  }
}
prob.home.away
```

```
## [1] 0.8093 0.9147 0.5072 0.7559 0.6288 0.9248 0.9508 0.7928
```

```
prob.home.away.df = data.frame(colnames(X.home))
prob.home.away.df$prob.home.bt.away = prob.home.away

colnames(prob.home.away.df) = c("Rank:Position", "Prob.home.bt.away")

kable(prob.home.away.df)
```

Rank:Position	Prob.home.bt.away
RankRank1:PositionPK	0.8093
RankRank2:PositionPK	0.9147
RankRank3:PositionPK	0.5072
RankRank4:PositionPK	0.7559
RankRank1:PositionQB	0.6288
RankRank2:PositionQB	0.9248
RankRank3:PositionQB	0.9508
RankRank4:PositionQB	0.7928

The above table shows that players perform better at home than away as expected.

Beta defense

If a player is facing a team which gives up more points to players on average, we expect the player will score more points.

```
Num.fixed.size=Num.Position*Num.fixed.pred
beta.defense = post.samp[, paste("beta.defense[",1:Num.fixed.size,"]", sep="")]

beta.defense.int.df = data.frame(colnames(X.defense))
beta.defense.int = matrix(rep(0, Num.fixed.size * 4), nrow=Num.fixed.size, ncol = 4)
```

```
int.alpha=0.05
for (p in 1:Num.Position) {
  for (f in 1:Num.fixed.pred) {
    idx = (f-1) * Num.Position + p
      beta.defense.int[idx, 1:3] =  quantile(beta.defense[, idx], c(int.alpha/2, 0.5, 1-int.alpha/2))
      beta.defense.int[idx, 4] = mean(beta.defense[, idx])
  }
}

beta.defense.int.df$pct025 = beta.defense.int[, 1]
beta.defense.int.df$pct975 = beta.defense.int[, 3]
beta.defense.int.df$median = beta.defense.int[, 2]
beta.defense.int.df$mean = beta.defense.int[, 4]
colnames(beta.defense.int.df) = c("beta.defense.position", "pct025", "pct975", "median", "mean")
kable(beta.defense.int.df)
```

beta.defense.position	pct025	pct975	median	mean
AvgOppPAP7Wks:PositionPK	-0.0663	0.5435	0.2350	0.2347
AvgOppPAP7Wks:PositionQB	-0.2931	0.1377	-0.0741	-0.0750

We observe that the median beta.defense for PK is positive as expected. But for QB, it is negative, that implies QB actually scores less against bad defensive team.

DIC

```
(dic.samp = dic.samples(m, NTotalSim))
```

```
## Mean deviance:  4700
## penalty 19
## Penalized deviance: 4719
```

The effective number of parameters("penalty") is 19, and the Plummer's DIC ("Penalized deviance") is 4719. Not that we have 29 parameters in our model, 10 of them were shrunk away.

Posterior Predictive Check

Error correlation Check

A posterior predictive p-value using the following test quantity

$$T(y, X, \theta) = |\hat{cor}(\epsilon, \text{time})|$$

where $\hat{cor}(\epsilon, \text{time})$ is sample correlation between the error vector ϵ and the year week in the data. The larger this quantity is for the model, the less well it fits the data as that would mean the error is correlated with time.

The simulated error vectors ϵ (as rows of a matrix):

```
error.sim <- matrix(NA, NTotalSim, nrow(fdp_train))
y_hat.sim <- matrix(NA, NTotalSim, nrow(fdp_train))
for(s in 1:NTotalSim) {
  y_hat.sim[s, ] =  fdp_train$AvgPts5Wks + (X.defense %*% beta.defense[s, ]) + (X.home %*% beta.home[s,
  error.sim[s, ] <- (fdp_train$FanDuelPts - y_hat.sim[s, ])
}
```

The simulated replicate error vectors ϵ^{rep} (as rows of a matrix), which are the error vectors computed using replicate response vectors y^{rep}:

```
post.sigma.2.sim <- post.samp[,"sigmasq"]
post.sigma.sim <- sqrt(post.sigma.2.sim)

yreps <- matrix(NA, NTotalSim, nrow(fdp_train))
for(s in 1:NTotalSim) {
  yreps[s, ] <- rnorm(nrow(fdp_train), y_hat.sim[s, ], post.sigma.sim[s])
}

error.rep <- matrix(NA, NTotalSim, nrow(fdp_train))

for(s in 1:NTotalSim) {
  error.rep[s, ] <- (yreps[s, ] - y_hat.sim[s, ])
}
```

The simulated values of $T(y, X, \theta)$

```
T.sim = abs(cor(t(error.sim), fdp_train$YearWeek))
head(T.sim)
```

```
##          [,1]
## [1,] 0.06068
## [2,] 0.06559
## [3,] 0.06371
## [4,] 0.05732
## [5,] 0.06541
## [6,] 0.06032
```

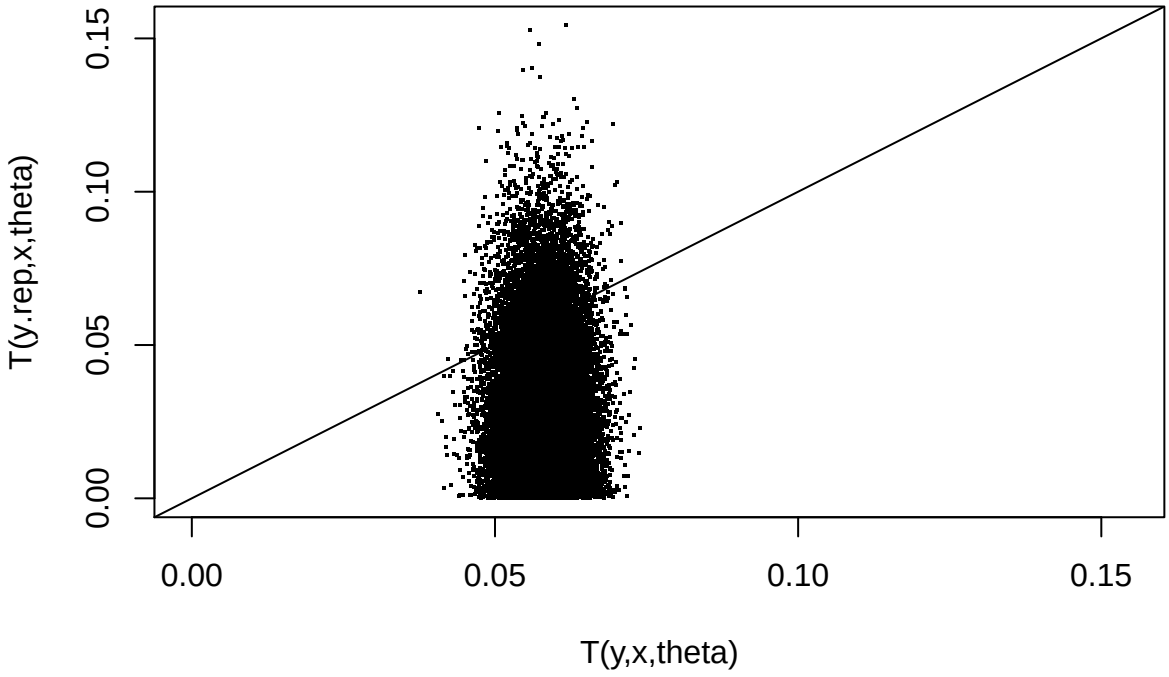
The simulated values of $T(y^{rep}, X, \theta)$

```
T.rep.sim = abs(cor(t(error.rep), fdp_train$YearWeek))
head(T.rep.sim)
```

```
##           [,1]
## [1,] 0.001265
## [2,] 0.028902
## [3,] 0.001193
## [4,] 0.095528
## [5,] 0.035466
## [6,] 0.003518
```

The simulated values of $T(y^{rep}, X, \theta)$ versus those of $T(y, X, \theta)$, with a reference line indicating where the two values would be equal.

```
plot(T.sim, T.rep.sim, pch=".", cex=2,
  xlim=c(min(T.sim, T.rep.sim), max(T.sim, T.rep.sim)),
  ylim=c(min(T.sim, T.rep.sim), max(T.sim, T.rep.sim)),
  xlab="T(y,x,theta)", ylab="T(y.rep,x,theta)")
abline(a=0,b=1)
```



The posterior predictive p-value:

```
(p.value = mean(T.rep.sim >= T.sim))
```

```
## [1] 0.1162
```

The p.value is 0.1162, > 0.05, which does not indicate any evidence of problem.

Chi-square Discrepancy Check

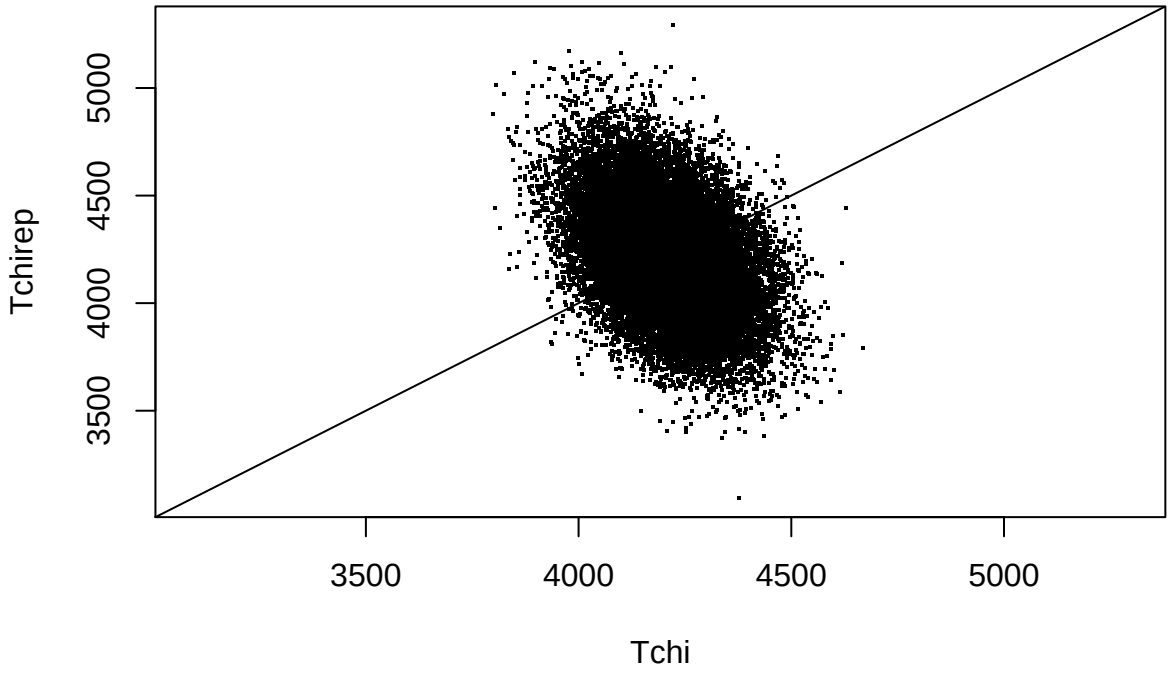
Chi-square discrepancy check is used to check for general model issues like mis-specified means, mis-specified variances, and over-concentrated prior.

```
Tchi <- numeric(NTotalSim)
Tchirep <- numeric(NTotalSim)
for(s in 1:NTotalSim){
  Tchi[s] <- sum((fdp_train$FanDuelPts - y_hat.sim[s,])^2 / post.sigma.sim[s])
  Tchirep[s] <- sum((yreps[s,] - y_hat.sim[s,])^2 / post.sigma.sim[s])
```

```
}
(p.value.Tchi = mean(Tchirep >= Tchi))
```

```
## [1] 0.5057
```

```
plot(Tchi, Tchirep, pch=".", cex=2,
  xlim=c(min(Tchi, Tchirep), max(Tchi, Tchirep)),
  ylim=c(min(Tchi, Tchirep), max(Tchi, Tchirep)),
  xlab="Tchi", ylab="Tchirep")
abline(a=0,b=1)
```



The posterior predictive p-value using the chi-square discrepancy is `p.value.Tchi`=0.5057. The p-value is $>$ 0.05. Hence, it does not indicate any evidence of problems.

Individual Data Point Discrepancy Check

Using $Pr(y^{rep} \geq y|y)$ as posterior predictive p-value

```
yreps.minus.y <- matrix(NA, NTotalSim, nrow(fdp_train))
for(s in 1:NTotalSim) {
  yreps.minus.y[s, ] <- yreps[s, ] - fdp_train$FanDuelPts
}

(p.value.y.rep.all = mean(yreps.minus.y > 0))
```

```
## [1] 0.5076
```

The posterior predictive p-value using individual data point is `p.value.y.rep.all` = 0.5076, which is > 0.05. This shows no evidence of problem.

Non Negative Check

As discussed in the model section, we use normal distribution, instead of Poisson distribution, to simplify the model. Here we'll check the portion of predicted value < 0.

```
perct.lt.zero = mean(yreps < 0)
```

The percentage of predicted values that are less than zero is `perct.lt.zero` = 0.0463, which is relatively small. This justify the decision to use normal to simplify our model.

Prediction

We use the last week of data to check the prediction effectiveness of the model. This is essentially a cross validation analysis.

```
if (Num.Position == 1) {
  #X.defense = model.matrix(~ 0 + AvgOppPAP7Wks + FanDuelSalary, data=fdp_train)
  X.defense.test = model.matrix(~ 0 + AvgOppPAP7Wks, data=fdp_test)
  if (Use.Rank) {
    X.home.test = model.matrix(~ 0 + Rank , data=fdp_test)
    X.away.test = model.matrix(~ 0 + Rank , data=fdp_test)
  } else {
    X.home.test = rep(1, nrow(fdp_test))
    X.away.test = rep(1, nrow(fdp_test))
  }
} else {
  #X.defense = model.matrix(~ 0 + AvgOppPAP7Wks:Position + FanDuelSalary:Position, data=fdp_train)
  X.defense.test = model.matrix(~ 0 + AvgOppPAP7Wks:Position, data=fdp_test)
  if (Use.Rank) {
    X.home.test = model.matrix(~ 0 + Rank:Position , data=fdp_test)
    X.away.test = model.matrix(~ 0 + Rank:Position , data=fdp_test)
  } else {
    X.home.test = model.matrix(~ 0 + Position , data=fdp_test)
    X.away.test = model.matrix(~ 0 + Position , data=fdp_test)
  }
}


X.home.test = X.home.test * fdp_test$HomeGame
X.away.test = X.away.test * (1- fdp_test$HomeGame)
X.test = cbind(X.defense.test, X.home.test, X.away.test)
```

```
y_hat.test <- matrix(NA, NTotalSim, nrow(fdp_test))
for(s in 1:NTotalSim) {
  y_hat.test[s, ] =  fdp_test$AvgPts5Wks + (X.defense.test %*% beta.defense[s, ]) + (X.home.test %*% be
}
```

```
y.pred <- matrix(NA, NTotalSim, nrow(fdp_test))
for(s in 1:NTotalSim) {
  y.pred[s, ] <- rnorm(nrow(fdp_test), y_hat.test[s, ], post.sigma.sim[s])
}
```

Prediction of Individual Player Performance

A measure of the effectiveness of this model is to predict individual player performance. Consider an example data point, `fdp_test[1,]`

```
(fdp_test[1,])
```

```
##    Position Year YearWeek Opponent Week PlayerId       Name     Team HomeGame
## 37       QB 2016   201615  Broncos   15     1131 Brady, Tom Patriots        0
##    FanDuelPts FanDuelSalary AvgOppPAP7Wks SdOppPAP7Wks OallAvgPAP OallStdevPAP
## 37       7.42          8100         12.24        6.266      17.44        2.909
##    AvgPts5Wks StdevPts5Wks OffRnk5Wks DefRnk7Wks  Rank
## 37      20.36        7.192      Rank1      Rank4 Rank1
```

The real FanDuelPts is 7.42

The predicted value has the following 95% interval

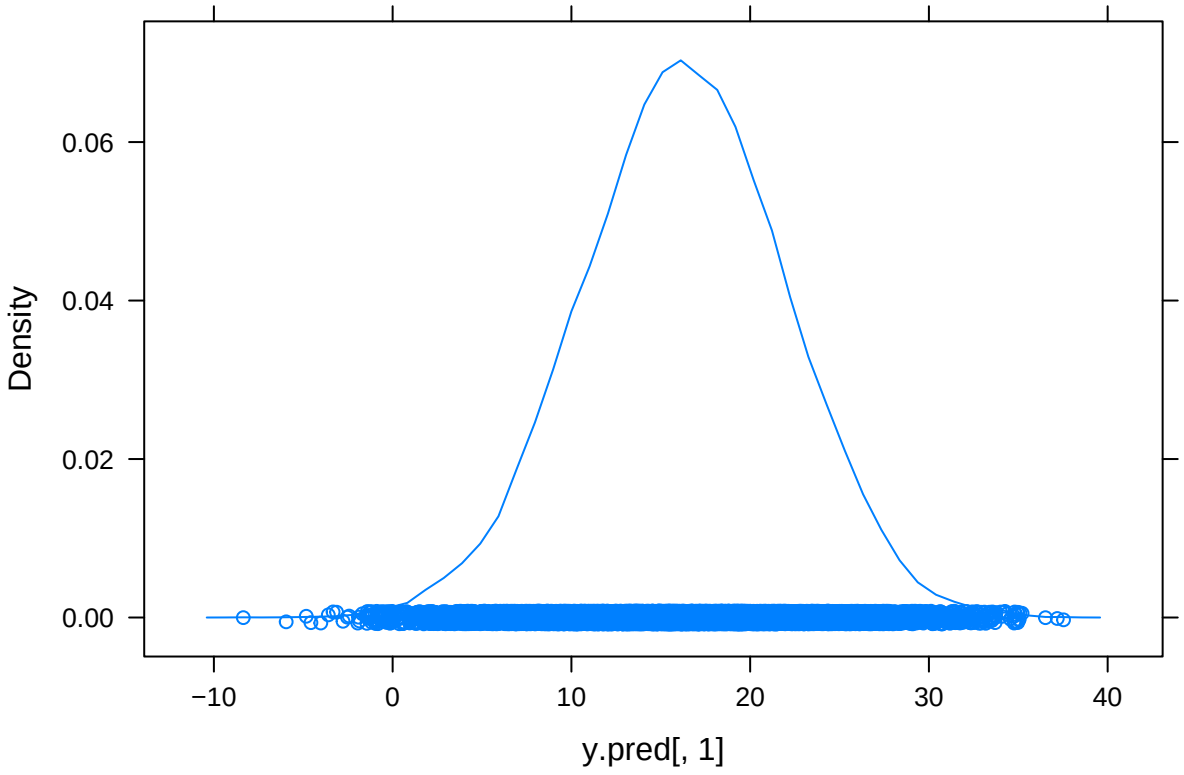
```
quantile(y.pred[, 1], c(0.025, 0.975))
```

```
##   2.5%  97.5%
##  4.944 27.266
```

which does contain the actual data value of 7.42

Here is the density plot of the posterior density

```
library(lattice)
densityplot(y.pred[, 1])
```



Overall Prediction Effectiveness

To measure the overall prediction effectiveness, we can look at $Pr(y_{pred} >= y)$ as a posterior p-value.

```
y.pred.minus.y <- matrix(NA, NTotalSim, nrow(fdp_test))
for(s in 1:NTotalSim) {
  y.pred.minus.y[s, ] <- y.pred[s, ] - fdp_test$FanDuelPts
}

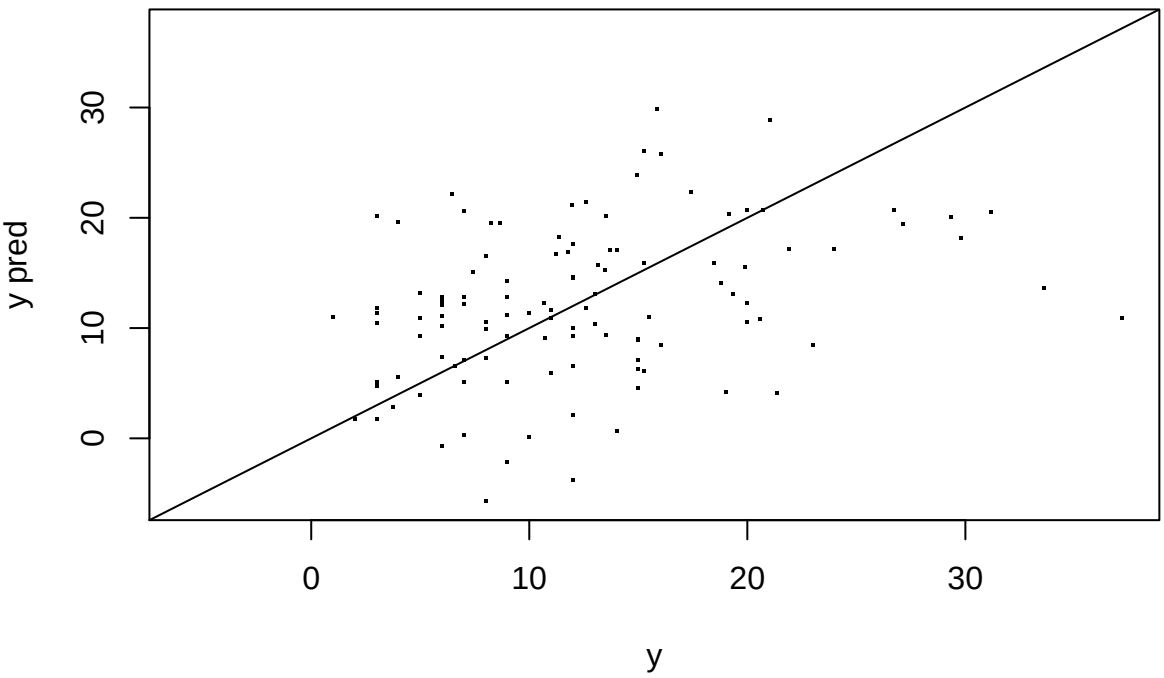
(p.value.y.pred.all = mean(y.pred.minus.y > 0))
```

```
## [1] 0.4683
```

The probability of $y_{pred} >= y$ is 0.4683, close to 0.5, which implies a relatively good predictive value.

A look at a cross section of how one simulation of a prediction of the whole test set

```
for (s in 1:1) {
  plot(fdp_test$FanDuelPts, y.pred[s, ], pch=".", cex=2,
  xlim=c(min(y.pred[s, ], fdp_test$FanDuelPts), max(y.pred[s, ], fdp_test$FanDuelPts)),
  ylim=c(min(y.pred[s, ], fdp_test$FanDuelPts), max(y.pred[s, ], fdp_test$FanDuelPts)),
  xlab="y", ylab="y pred")
  abline(a=0,b=1)
}
```


y pred
0
10
20
30
0
10
20
30
y

Alternative Model - no rank

```
#sink("fdp.norank.bug")
#cat("
model {
  for (i in 1:length(y)) {
    y[i] ~ dnorm(alpha[i] + inprod(X.defense[i, ], beta.defense)
                 + inprod(X.home[i, ], beta.home)
                 + inprod(X.away[i, ], beta.away), sigmasqinv)
  }

  # The entry of the beta.defense corresponds to Opponent:Position
  # In our model, we pool the beta.defense based on position.
  # i.e. All defense effects of the same position are drawn from the same distribution
  for (p in 1:Num.Position) {
    beta.defense[p] ~ dnorm(delta[p], 1/1000^2)
    delta[p] ~ dnorm(0, 1/100000^2)
  }

  # The entry of the beta.home and beta.away corresponds to Position
  # In our model, we pool the beta.home/away based on Position
  # NO RANK
  for (t in 1:Num.Position) {
    beta.home[t] ~ dnorm(eta, 1/1000^2)
    beta.away[t] ~ dnorm(rho, 1/1000^2)
  }
  eta ~ dnorm(0, 1/100000^2)
  rho ~ dnorm(0, 1/100000^2)

  sigmasqinv ~ dgamma(0.0001, 0.0001)
  sigmasq <- 1/sigmasqinv
}
#    ",fill = TRUE)
#sink()
```

```
Use.Rank = FALSE
Num.Opponent = length(unique(fdp_train[, "Opponent"]))
Num.Position = length(unique(fdp_train[, "Position"]))
#Num.fixed.pred=2 #AvgOppPAP7Wks + FanDuelSalary
Num.fixed.pred=1 #AvgOppPAP7Wks
if (Use.Rank) {
  Num.Rank = length(unique(fdp_train[, "Rank"]))
  Num.HomeAwayInit = Num.Rank
  Model.File.Ext = ""
} else {
  Num.HomeAwayInit = 1
  Model.File.Ext = ".norank"
}


if (Num.Position == 1) {
  #X.defense = model.matrix(~ 0 + AvgOppPAP7Wks + FanDuelSalary, data=fdp_train)
  X.defense = model.matrix(~ 0 + AvgOppPAP7Wks, data=fdp_train)
```

```
  if (Use.Rank) {
    X.home = model.matrix(~ 0 + Rank , data=fdp_train)
    X.away = model.matrix(~ 0 + Rank , data=fdp_train)
  } else {
    X.home = rep(1, nrow(fdp_train))
    X.away = rep(1, nrow(fdp_train))
  }
} else {
  #X.defense = model.matrix(~ 0 + AvgOppPAP7Wks:Position + FanDuelSalary:Position, data=fdp_train)
  X.defense = model.matrix(~ 0 + AvgOppPAP7Wks:Position, data=fdp_train)
  if (Use.Rank) {
    X.home = model.matrix(~ 0 + Rank:Position , data=fdp_train)
    X.away = model.matrix(~ 0 + Rank:Position , data=fdp_train)
  } else {
    X.home = model.matrix(~ 0 + Position , data=fdp_train)
    X.away = model.matrix(~ 0 + Position , data=fdp_train)
  }
}


X.home = X.home * fdp_train$HomeGame
X.away = X.away * (1- fdp_train$HomeGame)
X = cbind(X.defense, X.home, X.away)
```

```
# Initialization List for the 4 chains
jags.inits=list(
  list( sigmasqinv=    0.01,  delta = rep(-100000, Num.Position * Num.fixed.pred),
        eta = c(100000, -100000, 100000, -100000)[1:Num.HomeAwayInit],
        rho = c(-100000, 100000, -100000, 100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 ),
  list( sigmasqinv=    0.01,  delta = rep(100000, Num.Position * Num.fixed.pred),
        eta = c(100000, -100000, -100000, 100000)[1:Num.HomeAwayInit],
        rho = c(-100000, 100000, 100000, -100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 + 1 ),
  list( sigmasqinv=0.000001,  delta = rep(-100000, Num.Position * Num.fixed.pred),
        eta = c(-100000, 100000, -100000, 100000)[1:Num.HomeAwayInit],
        rho = c(100000, -100000, 100000, -100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 + 2 ),
  list( sigmasqinv=0.000001,  delta = rep(100000, Num.Position * Num.fixed.pred),
        eta = c(-100000, 100000, 100000, -100000)[1:Num.HomeAwayInit],
        rho = c(100000, -100000, -100000, 100000)[1:Num.HomeAwayInit],
        .RNG.name = "base::Mersenne-Twister", .RNG.seed = 20171008 + 3 )
)

data.jags <- list(
  y= fdp_train$FanDuelPts,
  alpha = fdp_train$AvgPts5Wks,
  X.defense = X.defense,
  X.home = X.home,
  X.away = X.away,
  Num.fixed.pred=Num.fixed.pred,
  Num.Position=Num.Position
  #Num.Opponent=Num.Opponent,
```

```
  #Num.Rank=Num.Rank
)
```

```
runModel=TRUE
runSample=TRUE

mon.col <- c("delta", "eta", "rho", "beta.defense", "beta.home", "beta.away", "sigmasq")

NSim = 30000
NChain = 4
NThin = 5
NTotalSim = NSim * NChain / 5
if (runModel) {
  if(Use.Rank) {
    bug.file = "fdp.bug"
  } else {
    bug.file = "fdp.norank.bug"
  }
  m <- jags.model(bug.file, data.jags, inits = jags.inits, n.chains=NChain, n.adapt = 1000)
  save(file=paste("fdp.jags.model.init", Model.File.Ext, ".Rdata", sep=""), list="m")
} else {
  load(paste("fdp.jags.model.init", Model.File.Ext, ".Rdata", sep=""))
  m$recompile()
}
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 746
##    Unobserved stochastic nodes: 11
##    Total graph size: 9356
##
## Initializing model
```

```
load.module("dic")

N.Retry.Loop = 1
if (runSample) {
  N.burnin=2500/2
  for (loopIdx in 1:N.Retry.Loop) {
    (start_time <- Sys.time())
    (N.burnin = N.burnin * 2)
    result = burnAndSample(m, N.burnin, NSim, show.plot=FALSE, mon.col = mon.col, n.thin=NChain)
    (end_time <- Sys.time())
    (result$gelman.R.max)
  }
  run.params = paste(".", N.burnin, ".", NChain, ".", NSim, ".", NThin, sep="")
  save(file=paste("fdp.jags.samples", run.params, Model.File.Ext, ".Rdata", sep=""), list="result")
  save(file=paste("fdp.jags.model", run.params, Model.File.Ext, ".Rdata", sep=""), list="m")
} else {
  N.burnin=2500/2 * (2**N.Retry.Loop)
  run.params = paste(".", N.burnin, ".", NChain, ".", NSim, ".", NThin, sep="")
```

```
  load(paste("fdp.jags.samples", run.params, Model.File.Ext, ".Rdata", sep=""))
  load(paste("fdp.jags.model", run.params, Model.File.Ext, ".Rdata", sep=""))
  m$recompile()
  gelman.diag(result$coda.sam, autoburnin=FALSE, multivariate = FALSE)
}
```

Converged as `gelman.R.max` $= 1.0017 < 1.1$ and the plot also looks good.

```
(m.summary = summary(result$coda.sam))
```

```
##
## Iterations = 2504:32500
## Thinning interval = 4
## Number of chains = 4
## Sample size per chain = 7500
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                     Mean       SD Naive SE Time-series SE
## beta.away[1]    -2.4868    1.374 0.007933        0.02422
## beta.away[2]    -1.8561    2.094 0.012089        0.05400
## beta.defense[1]  0.2522    0.162 0.000933        0.00293
## beta.defense[2]  0.0178    0.114 0.000659        0.00299
## beta.home[1]    -1.5692    1.352 0.007806        0.02381
## beta.home[2]    -0.3188    2.044 0.011800        0.05241
## delta[1]         5.7158 1003.464 5.793504        5.82433
## delta[2]        -9.5228 1004.742 5.800878        5.80110
## eta             -1.4774  709.925 4.098752        4.07614
## rho             -3.8073  703.095 4.059322        4.07909
## sigmasq         35.2576    1.836 0.010603        0.01070
##
## 2. Quantiles for each variable:
##
##                       2.5%       25%     50%      75%    97.5%
## beta.away[1]       -5.1688   -3.4072 -2.4840  -1.5705    0.226
## beta.away[2]       -5.9390   -3.2664 -1.8725  -0.4445    2.312
## beta.defense[1]    -0.0665    0.1436  0.2530   0.3604    0.568
## beta.defense[2]    -0.2074   -0.0592  0.0183   0.0946    0.240
## beta.home[1]       -4.2070   -2.4793 -1.5684  -0.6617    1.090
## beta.home[2]       -4.2767   -1.7074 -0.3297   1.0538    3.712
## delta[1]        -1963.6012 -667.1541  2.2090 687.1508 1975.654
## delta[2]        -1994.6211 -688.6346 -4.0685 670.0538 1930.427
## eta             -1393.1374 -478.2809 -2.4320 476.9654 1390.406
## rho             -1390.2689 -479.6002 -3.7107 470.8765 1368.090
## sigmasq            31.8231   34.0001 35.1910  36.4582   39.015
```

Effective Sample Size

```
(eff.size = effectiveSize(result$coda.sam[, ]))
```

```
##    beta.away[1]    beta.away[2] beta.defense[1] beta.defense[2]    beta.home[1]
```

```
##            3228            1505            3051            1453            3238
##  beta.home[2]       delta[1]       delta[2]             eta             rho
##            1521           29696           30000           30402           29716
##         sigmasq
##           29489
```

The effective sample sizes of all parameters are greater than 400.

DIC

```
(dic.samp = dic.samples(m, NTotalSim))
```

```
## Mean deviance:  4774
## penalty 7.02
## Penalized deviance: 4781
```

The effective number of parameters("penalty") is 7.02, and the Plummer's DIC ("Penalized deviance") is 4781. This model has a higher DIC compared with the original one with rank(4719). Hence, we conclude that the original model (with rank) is better for prediction.

Results

The model has decent prediction ability. It should be noted that we only picked two positions to predict due to computation resource constraint. In the pursue of creating this model, we have multiple route:

1) We have tried to include all positions. However, the model took 5 hours to finish the MCMC simulation. Therefore, we elected to include a smaller subset.
2) We have tried to include FanDuelSalary as a predictor. However, that does not improve the model, and added sufficient time to compute - About 30 minutes to compute.

Contributions

All three members contribute roughly the same amount of works. While each member owns certain pieces of the project, all members contribute idea, and review all parts of the project. The following list summarizes the main contribution of individual member:

- **Aaron Ray** (aaronwr2@illinois.edu) - Came up with the project idea, the primary goals, data discovery and attribution.
- **Kiomars Nassiri** (nassiri2@illinois.edu) - Presentation and various documentation.
- **Michael Chan** (mhchan3@illinois.edu) - Finalize data cleansing, drive the design, implementation, and the analysis of the model.

Reference

The analysis is inspired by the study presented in the article, **Bayesian Hierarchical Modeling Applied to Fantasy Football Projections for Increased Insight and Confidence**, by Scott Rome.

Appendices

- Add data cleaning code here